



## Social Trust and Self-Rated Health in US Communities: a Multilevel Analysis

S. V. Subramanian, Daniel J. Kim, and Ichiro Kawachi

**ABSTRACT** *This study assessed the contextual and individual effects of social trust on health. Methods consisted of a multilevel regression analysis of self-rated poor health among 21,456 individuals nested within 40 US communities included in the 2000 Social Capital Community Benchmark Survey. Controlling for demographic covariates, a strong income and education gradient was observed for self-rated health. Higher levels of community social trust were associated with a lower probability of reporting poor health. Individual demographic and socioeconomic predictors did not explain the association of community social trust with self-rated health. Controlling for individual trust perception, however, rendered the main effect of community social trust statistically insignificant, but a complex interaction effect was observed, such that the health-promoting effect of community social trust was significantly greater for high-trust individuals. For low-trust individuals, the effect of community social trust on self-rated health was the opposite. Using the latest data available on community social trust, we conclude that the role of community social trust in explaining average population health achievements and health inequalities is complex and is contingent on individual perceptions of social trust. Future multilevel investigations of social capital and population health should routinely consider the cross-level nature of community or neighborhood effects.*

### INTRODUCTION

Social capital is defined as those features of social structures (such as trust, norms, and sanctions), appropriable social institutions, and information channels that facilitate collective action.<sup>1</sup> This definition is contested (see, e.g., reference 2) and evolving, but most versions encompass two components of the concept of social capital: the structural and the cognitive. The *structural component* of social capital includes the extent and intensity of associational links and activity in society (e.g., density of civic associations, measures of informal sociability, indicators of civic engagement). The *cognitive component* assesses people's perceptions of the level of interpersonal trust, sharing, and reciprocity.<sup>3</sup>

Social capital, meanwhile, has been linked to economic development, the smooth functioning of democracies, and the prevention of crime, among other benefits.<sup>4</sup> Recently, the notion of social capital has been extended to the population health field to explain variations in the health achievement of communities and societies.<sup>5</sup>

Drs. Subramanian, Kim, and Kawachi are with the Department of Health and Social Behavior, Harvard School of Public Health.

Correspondence: Dr. S. V. Subramanian, Department of Health and Social Behavior, Harvard School of Public Health, 677 Huntington Avenue, 7th Floor, Boston, MA 02115. (E-mail: svsubram@hsph.harvard.edu)

Indicators of social capital are, however, not routinely available on administrative data sets (such as the government census). Consequently, to tap into indicators of the concept, researchers have resorted to the use of secondary sources, such as the density of membership in civic associations, national opinion poll data on interpersonal trust, and perceptions of reciprocity.<sup>6</sup> Following the example of the political scientist, Robert Putnam,<sup>4</sup> US researchers have analyzed state-level data from the National Opinion Research Center's General Social Surveys on interpersonal trust, norms of reciprocity, and membership in voluntary associations. When correlated with state-level health indicators, these social capital variables were found to account for a significant portion of the cross-sectional variations in mortality rates across states of the United States.<sup>7</sup> For instance, the level of mistrust (the proportion of residents in a state who agreed that "most people would take advantage of you") has been shown to be strikingly correlated with average age-adjusted mortality rates ( $r = 0.79$ ,  $P < .001$ ). Lower levels of trust were associated with higher rates of most major causes of death, including heart disease, cancers, infant mortality, and violent deaths, including homicide. An increase of 1 standard deviation in trust was associated with about a 9% lower level of overall mortality. Similar associations were found between death rates and other indicators of social capital, including norms of reciprocity (the proportion of residents agreeing that "most of the time, people try to be helpful"), as well as per capita membership in a variety of civic associations. The association of social capital indicators with mortality remained after accounting for state differences in median income and poverty rates.

Social capital is associated with mortality and with more general indicators of health status. Using data among 167,259 respondents in the Centers for Disease Control Behavioral Risk Factor Surveillance Surveys, a strong correlation was found<sup>8</sup> between social mistrust and the proportion of residents in each state who rated their own health as being only "fair or poor" as opposed to "excellent, very good, or good" ( $r = 0.71$ ,  $P < .0001$ ). These associations persisted after controlling for individual-level factors that could account for poor health status.<sup>9</sup> After taking account of individual-level differences in variables such as health insurance coverage, personal income, educational attainment, race/ethnicity, cigarette smoking, and obesity, residence in a state with low social capital was still associated with about a 40% excess risk of reporting poor health.

In the Project on Human Development in Chicago Neighborhoods,<sup>10</sup> a data set based on a survey of 343 neighborhood clusters of the city of Chicago, Illinois, community variations in interpersonal trust, reciprocity, and group membership were significantly correlated with overall and cause-specific mortality rates, even after controlling for levels of socioeconomic deprivation.<sup>11</sup>

The hypothesized mechanisms linking social capital to health have been reviewed by Kawachi and Berkman.<sup>5</sup> For example, higher levels of interpersonal trust between residents of a neighborhood may result in the quicker diffusion and uptake of health-promoting innovations (e.g., a new screening test for prostate cancer) through established information channels. Trust between neighbors is also a necessary ingredient for voluntarism and collective action. For instance, residents may donate their time for community service (e.g., a grassroots campaign to protest the closure of a local hospital) with the expectation that their altruistic actions will be reciprocated by others at a future point in time. Finally, parents in a community who know and trust one another may be more effective at exercising informal social control over the deviant health behaviors of each other's children, such as smoking and alcohol abuse.

What remains to be determined, however, is whether social capital at the community level is an independent determinant of health after taking account of individual residents' assessments of the level of social capital within their communities. This problem is especially pertinent to measures of cognitive social capital, such as neighborhood variations in interpersonal trust, which are themselves measured by aggregating individual perceptions of their neighbors' trustworthiness. This problem raises two questions: Is there a true contextual variation in a community's level of social capital after taking account of individual compositional characteristics (e.g., characteristics such as socioeconomic status and race that may influence a resident's cognitive assessment of trust)? Is there a contextual effect of community social capital on health after taking account of individual differences in trust? We addressed the first question in a recent analysis based on the 1994–1995 Community Survey of the Project on Human Development in Chicago Neighborhoods (PHDCN).<sup>12</sup> Using multilevel analysis, we found that, even after accounting for individual demographic (age, sex, race, marital status) and socioeconomic characteristics (income, educational attainment), significant neighborhood differences remained in levels of interpersonal trust, supporting the notion of social capital as a true contextual construct.

In the present study, we turned to the second question, that is, whether community levels of trust exert a contextual influence on health after taking account of individual residents' perceptions of the trustworthiness of others in their community. The 2000 Social Capital Community Benchmark Survey ([www.ksg.harvard.edu/saguaro/communitysurvey](http://www.ksg.harvard.edu/saguaro/communitysurvey)), developed by the Saguaro Seminar at Harvard University (Cambridge, MA) allows for the measurement of health and social trust at both individual and aggregate levels across US communities. Specifically, using a multilevel perspective, the article examines (1) the average relationship between individual self-rated health and individual sociodemographic and socioeconomic factors across 40 US communities; (2) the extent to which individual sociodemographic and socioeconomic factors account for community variations in self-rated health; (3) the average relationship between community social trust (measured by aggregating individual responses to a question about interpersonal trust) and population health; (4) the extent to which this average cross-level relationship between community trust and individual health is an artifact of individual perceptions of social trust; and (5) how the effect of community social trust on population health is different across levels of perceived individual trust perceptions.

## METHODS

### Sources of Data

The analysis was based on the 2000 Social Capital Community Benchmark Survey. This survey was one of the first attempts to characterize "social capital" across diverse communities of the United States and to establish benchmarks for future monitoring and possible intervention. In terms of selecting the communities, all community foundations attending the annual meeting of US community foundations in 1999 were invited to apply. From the communities applying, 34 local community foundations were selected that broadly represented the diversity of communities across the country (smaller and bigger towns, regions of the country, etc.) (T. Sander, personal communication, Harvard University, Cambridge, MA, 2002). Each sponsoring community organization then decided what specific area(s) to be

surveyed, how many interviews to conduct, and if specific areas or ethnic groups were to be oversampled.<sup>13</sup> Most of the samples ranged between 500 and 1,500 interviews. The survey was conducted by telephone by TNS Intersearch (Philadelphia, PA) using random-digit dialing (RDD) among the 40 US communities in the year 2000 and in early 2001. It may be noted that some community foundations operated in more than one community. Telephone interviews averaged 26 minutes in length, and the participation rates within community samples (i.e., the proportion of those eligible who responded to the survey) ranged from a low of 30.2% (Denver, CO) to a high of 57.2% (Newaygo County, MI).<sup>13</sup> In the majority of cases, the survey area was a single county or a cluster of contiguous counties; community samples ranged from municipalities to entire states, suggesting a marked variation in ways communities were identified and defined. All survey data were provided by the Roper Center for Public Opinion Research (Storrs, CT).

### **Outcome Measures**

Our outcome was the self-reported overall health status of individuals. This was determined by people's response to the following question: "How would you describe your overall state of health these days? Would you say it is excellent, very good, good, fair, or poor?" To facilitate comparison with previous research, we collapsed the fivefold categories to form a dichotomous outcome of self-rated health: 0 for excellent, very good, or good and 1 for fair or poor. In other words, we analyzed the probability of reporting fair/poor health.

### **Independent Variables**

At the individual level, we considered key sociodemographic (age, gender, race, marital status) and socioeconomic (educational attainment, income) characteristics. Perceptions of individual trust were derived by summing individual responses to questions on (1) general interpersonal trust ("whether most people can be trusted") with the potential responses being "people can be trusted," "you can't be too careful," and (volunteered) "depends"; and (2) degrees of trustworthiness of neighbors, coworkers, fellow congregants, store employees where the individual shops, and local police ("how much you can trust people"), with the potential responses being "trust them a lot," "trust them some," "trust them a little," and "trust them not at all." Individual scores on this interpersonal trust scale were dichotomized as low and high, using the average as the cut point.

At the community level, we considered a contextual social trust variable (measured on a continuous scale) aggregated from individual responses to questions on interpersonal trust. Values were calculated as the average of the standardized responses to the questions, using the US average of the response to each question for standardization. Aggregate community-level measures of social trust were calculated by taking the arithmetic average of the weighted individual-level measures. For a detailed account of the weighting procedure, see reference 13.

### **Statistical Analyses**

The statistical modeling framework anticipates that the individual ratings of self-rated health are partly dependent on the spatial communities to which they belong. This dependency in the response was modeled by partitioning the individual and community sources of variation. The spatial communities, meanwhile, were seen as a sample of the population of spatial communities in the United States. Such a perspective enabled us to make inferences about the population of spatial communi-

ties (rather than drawing inferences only for the communities considered in the survey) in addition to making inferences about the population of individuals.

Multilevel statistical techniques provide a technically robust framework, among others, to analyze the dependent nature of the outcome variable.<sup>14,15</sup> The principles underlying multilevel modeling procedures have been extensively discussed elsewhere.<sup>16</sup> In the context of the analysis presented here, the multilevel techniques allow estimation of (1) the overall relationships between individual factors and self-rated health across all communities (“fixed parameters”), (2) the variation between communities in self-rated health that cannot be accounted for by these factors (“random parameters”), and (3) the effect of community level predictors on self-rated health and how this effect can vary for different individual (compositional) characteristics (“fixed parameters”).

Since the response is binary, a multilevel logistic model based on a logit-link function was used.<sup>17</sup> Models were fitted using the *MLwiN* program<sup>18</sup> (Version 1.10.0006) with predictive/penalized quasi likelihood approximation with a second-order Taylor linearization procedure.<sup>19</sup> All models were estimated using the logit (logarithm of the odds) function. For interpretation, we used proportion, odds ratio (OR), or both. The following four models were sequentially developed:

*Model 1:* A two-level null (empty) model of individuals (level 1) nested within US communities (level 2) with no predictor variables in the fixed and the random parts of the model. Variation in self-rated health was partitioned across individuals (within communities) and between communities. This model provided a baseline for comparing the size of contextual variations in self-rated health in subsequent models.

*Model 2:* Same as model 1, but includes all the individual predictors (except individual trust) in the fixed part of the model. The model assessed the effect of individual predictors on self-rated poor health. Individual predictors were entered in the model in two sequential steps: first, the sociodemographic variables age, sex, race, and marital status were included (model 2A), and then socioeconomic status variables (educational attainment and income) were added (model 2B). The contextual variation in self-rated health between communities was estimated before and after taking into account the compositional effect of individual sociodemographic and socioeconomic variables.

*Model 3:* Same as model 2, but considers the fixed effect of community social trust on individual self-rated poor health and the extent to which it explains the community-level differences.

*Model 4:* Same as model 3, but considers the effect of interpersonal trust at the individual level to evaluate the relative importance of individual-level versus community-level social trust (model 4A). In addition, we also considered how the effect of community social trust on self-rated poor health differed for low- and high-trust individuals (model 4B).

## RESULTS

Table 1 provides a summary of the final data considered for the analysis. Except for age, individual characteristics were specified as categorical variables, with a base and a set of contrast indicator dummies. Age was centered about its mean, 45 years. This was done to have a meaningful interpretation of the base category. The total number of individual observations from 40 communities was 26,230. After excluding the missing data on the outcome and predictor variables, we conducted

**TABLE 1. Data description for the final sample**

Response		
Fair/poor health	Yes ( $n = 2,522$ , 11.8%)	No ( $n = 18,934$ , 88.2%)
Level 1, individuals, $n = 21,456$ : individual-level predictor variables		
Age (in years)	Mean = 45 years	Range = 18–89 years
Gender	Base: Male ( $n = 8,986$ , 41.9%)	Contrast: female ( $n = 12,470$ , 58.1%)
Ethnicity/race	Base: White ( $n = 16,691$ , 77.8%)	Contrast: black ( $n = 2,688$ , 12.5%) Other ( $n = 2,077$ , 9.7%)
Marital status	Base: Married ( $n = 10,901$ , 50.8%)	Contrast: single ( $n = 5,523$ , 25.7%) Separated/divorced ( $n = 3,578$ , 16.7%) Widowed ( $n = 1,454$ , 6.8%)
Educational attainment	Base: College and above ( $n = 7,430$ , 34.6%)	Contrast: less than high school ( $n = 1,469$ , 6.8%) High school ( $n = 5,551$ , 25.9%) Some college ( $n = 7,006$ , 32.7%)
Annual household income (in US\$)	Base: 100,000 and above ( $n = 2,617$ , 12.2%)	Contrast: 20,000 and less ( $n = 3,214$ , 15%) 20,000–30,000 ( $n = 3,208$ , 15%) 30,000–50,000 ( $n = 5,586$ , 26%) 50,000–75,000 ( $n = 4,413$ , 20.6%) 75,000–100,000 ( $n = 2,418$ , 11.3%)
Trust	Base: High trust ( $n = 12,282$ , 57.2%)	Contrast: low trust ( $n = 9,174$ , 42.8%)
Level 2, communities, $n = 40$ : community-level predictor variable		
Trust	Mean = 0.008	Range = –0.45 to 0.54

a multilevel regression analysis on 21,456 individuals nested within 40 US communities.

Table 2 presents the results of the multilevel models in the order in which they were developed. Converting the logit estimates from model 1 (the null model), we found that approximately 12% of the respondents, across all US communities, reported to be in poor health. The reference group in model 2B (Table 2)—the final model with all the individual sociodemographic and socioeconomic predictors—was a 45-year-old, white, married male, with the highest level of educational attainment belonging to the highest income category. For this group (the most advantaged socioeconomic group), the proportion reporting self-rated poor health was, on average, 3.4%. The independent differential effects (compared to the above reference group) of each individual variable are now presented. The main effect for each of the covariates was estimated after controlling for the remaining ones (see Table 2, model 2B).

As expected, age was linearly and positively associated with poor self-rated health such that older people were more likely to report being in poor health as compared to the young. No gender differences were observed on self-rated poor health, suggesting that men and women were both equally likely to report poor health. A statistically significant effect was observed for race. The probability of reporting poor health for black population groups was about 25% (OR = 1.25) higher than it was for whites. Other groups (non-white and non-black) were about 39% (OR = 1.39) more likely to report poor health compared to whites. Compared to married people, single and separated or divorced individuals were, on average, more likely to report poor health. Single people were 15% (OR = 1.15) more likely to report poor health compared to married people, and separated/divorced groups were 24% (OR = 1.24) more likely to report poor health. The widowed group showed no significant differences with the base group, married people.

We observed a significant gradient in the relationship between educational attainment and self-rated poor health. Population groups with the lowest level of educational attainment (the most disadvantaged socioeconomic group, i.e., less than high school) were more than three times likely (OR = 3.57) to report poor health (compared to the highest level of education, i.e., college and above). Populations with the middle level of education (i.e., high school completed) were approximately twice as likely (OR = 1.90) to report poor health. Statistically significant differences were also observed between groups with high educational levels (i.e., some college) (OR = 1.63) and the highest educational level (the reference group).

Controlling for educational attainment, we observed a statistically significant income gradient for self-rated poor health. The reference group was the richest income category (people with incomes more than \$100,000 per year). People with incomes less than \$20,000 per year (the lowest income category) had the largest differential probability of reporting poor health (OR = 4.04) compared to the highest income group, followed by income earners in the range \$20,000–\$30,000 (OR = 2.42), \$30,000–\$50,000 (OR = 1.72), and \$50,000–\$75,000 (OR = 1.31). No statistically significant differences were observed for the \$75,000–\$100,000 income group. We now turn to the findings on the amount of the community variation before and after taking into account the individual sociodemographic and socioeconomic factors.

The null model with no predictors (Table 2, model 1) revealed significant variation in self-reported poor health between communities ( $\sigma^2_{u0} = 0.045$ ). However,

**TABLE 2. Fixed and random part results for the multilevel analytical models (in logits)**

Fixed parameters	Model 1	Model 2A	Model 2B	Model 3	Model 4A	Model 4B
Constant	−2.030	−2.466	−3.344	−3.348	−3.509	−3.498
Individual predictors						
Sociodemographic						
Age (centered around 45)	0.027 (0.002)	0.022 (0.002)	0.022 (0.002)	0.022 (0.002)	0.026 (0.002)	0.026 (0.002)
Female	0.071* (0.045)	−0.015* (0.046)	−0.009* (0.047)	0.011* (0.047)	0.011* (0.047)	0.011* (0.047)
Black	0.467 (0.063)	0.231 (0.066)	0.207* (0.066)	0.037* (0.067)	0.050* (0.067)	0.050* (0.067)
Other	0.568 (0.072)	0.331 (0.074)	0.325 (0.074)	0.218 (0.075)	0.228 (0.075)	0.228 (0.075)
Single	0.394 (0.061)	0.144 (0.065)	0.154 (0.065)	0.135 (0.065)	0.134 (0.065)	0.134 (0.065)
Widowed	0.448 (0.079)	−0.078* (0.084)	−0.087 (0.084)	−0.091 (0.085)	−0.095* (0.085)	−0.095* (0.085)
Separated/divorced	0.499 (0.057)	0.222 (0.061)	0.219 (0.061)	0.184 (0.061)	0.180 (0.061)	0.180 (0.061)
Socioeconomic						
Low education		1.275 (0.084)	1.289 (0.084)	1.117 (0.086)	1.124 (0.086)	1.124 (0.086)
Middle education		0.644 (0.068)	0.658 (0.068)	0.564 (0.069)	0.568 (0.069)	0.568 (0.069)
High education		0.493 (0.065)	0.499 (0.065)	0.440 (0.066)	0.440 (0.066)	0.440 (0.066)
Less than \$20,000		1.398 (0.111)	1.396 (0.112)	1.326 (0.112)	1.330 (0.112)	1.330 (0.112)
\$20,000–30,000		0.887 (0.112)	0.884 (0.112)	0.823 (0.112)	0.828 (0.112)	0.828 (0.112)
\$30,000–50,000		0.544 (0.107)	0.546 (0.107)	0.510 (0.108)	0.513 (0.108)	0.513 (0.108)
\$50,000–75,000		0.271 (0.112)	0.276 (0.113)	0.256 (0.113)	0.257 (0.113)	0.257 (0.113)
\$75,000–100,000		0.233* (0.127)	0.228* (0.127)	0.217* (0.128)	0.219* (0.128)	0.219* (0.128)
Social capital						
Low trust				—	0.599 (0.050)	0.591 (0.050)
Community predictor						
Trust				−0.361 (0.175)	−0.141* (0.171)	−0.540 (0.217)
Individual/community interaction						
Low trust*Trust						0.847 (0.292)
Random parameters						
Level 3, between communities ( $\sigma_{u0}^2$ )	0.045 (0.015)	0.046 (0.015)	0.013* (0.007)	0.012* (0.007)	0.009* (0.007)	0.007* (0.006)

Figures in parentheses represent the standard errors.

All estimates are significant at .01 probability level or less, except those marked by \*, which have a probability greater than .01.



these community differences cannot be interpreted as evidence that communities matter in respect to themselves since the source of such differences could be simply due to individual composition. Assessing the community variations from model 2B (Table 2), it appears that between-community variations were an artifact of the individual compositional differences rather than “true” contextual differences between communities ( $\sigma^2_{u0} = 0.013$ ). Since we developed the models sequentially, it was possible to monitor which aspects of community composition accounted for the community differences. For instance, controlling for individual age, sex, race, and marital status did not explain away the community differences (Table 2, model 2A) in poor self-rated health ( $\sigma^2_{u0} = 0.046$ ). Indeed, the between-community variation hardly changed between model 1 and model 2A. It is only with the additional inclusion of individual education and income that the community variations disappeared, suggesting that the sampled communities are homogeneous in terms of their socioeconomic, rather than sociodemographic, composition. These findings have implications for the ways in which we conceptualize individual, compositional sources of variation and/or contextual sources of variation; we return to this issue in the discussion section.

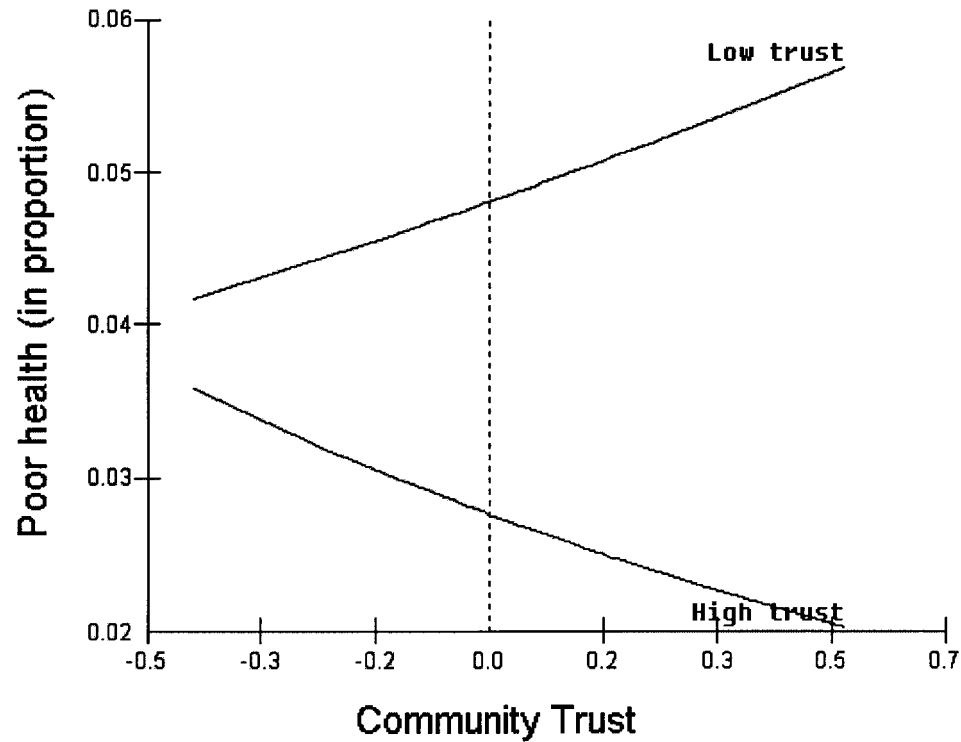
While the community variances were not significant, this does not necessarily imply an absence of community effects. Indeed, by not including the relevant community predictors, we could mis-specify the fixed part of a two-level statistical model. Consequently, having unpacked the role of individual demographic and socioeconomic factors on poor self-rated health, we considered the association between poor self-rated health and community levels of trust (a contextual predictor). Community level of trust was significantly and negatively associated with self-rated poor health (Table 2, model 3): in communities with higher levels of trust, individuals were less likely to report poor health after controlling for their demographic and socioeconomic characteristics.

Including individual trust perception rendered the main community effect of social capital statistically insignificant, suggesting that the aggregate social capital effect—previously reported in the literature—is an artifact of individual social capital perceptions (Table 2, model 4A). However, when explored further, a significant cross-level interaction effect between community social capital and individual trust was observed (Table 2, model 4B). Figure 1 plots the predicted relationship between community social capital ( $x$  axis) and probability of reporting poor health, converted to proportions ( $y$  axis), for low- and high-trust individuals based on results from model 4B. As can be seen, the protective effect of community social capital is present for high-trust individuals. For low-trust individuals, the effect is reversed, suggesting that high social capital communities are not particularly favorable for low-trust individuals.

While introducing individual trust did not change the effect of the remaining individual predictors, the differential observed for black became statistically insignificant. The white-black differential in self-rated health is somewhat confounded by the individual perceptions of trust. Indeed, in the sample, of a total of 2,688 blacks, 2,058 reported low trust, suggesting a strong correlation between the two.

## DISCUSSION

In this article, we examined the compositional and contextual sources of variation in self-rated health across 40 communities sampled in the 2000 Social Capital Community Benchmark Survey. At the individual level, we replicated previously ob-



**FIGURE 1** Predicted relationship between community social trust and individual self-rated poor health by low- and high-trust individuals.

Note: The slight bend of the lines in the graph is due to converting the logits to proportions and is not meant to suggest a non-linear relationship between community trust and poor health.

served relationships between certain demographic variables (older age, minority race/ethnic status, and being single/widowed/divorced) and poorer self-rated health. We also demonstrated the expected gradients between low income/low educational attainment and poor self-rated health. We found evidence of strong community clustering by individual income and educational attainment, such that this explained the major part of the between-community variation in poor self-rated health.

With regard to our main variable of interest, we found a main effect of community levels of social trust on self-rated health, which was significant even after accounting for individual demographic and socioeconomic status variables. However, when we controlled for individual trust perception, it rendered the main effect of community social trust statistically nonsignificant. On the other hand, there was a statistically significant complex interaction effect, such that the health-promoting effect of community social trust was significantly greater for high-trust individuals. For low-trust individuals, the effect of community social trust on self-rated health was in the opposite direction.

Our findings advance the empirical literature on social capital and health in two ways. First, our results imply that the contextual effect of community trust on self-rated health—reported in a previous study<sup>8</sup>—may be confounded by the compositional effect of individual trust perceptions. That is, places varied in terms

of levels of trust (and health achievement) because they were composed of individuals who are trusting or trustworthy. The “level of action” of social capital appeared to lie at the individual, not the community, level.

However, there is more to the story. A second way in which our study advances the empirical literature was through the specific examination of cross-level interactions. Here, we found a complex interaction between individual and community trust. Despite the absence of a main effect of community trust on self-rated health, we found that highly trusting individuals reported worse health if they resided in low-trust communities. Conversely, individuals reporting low levels of trust did not perceive better health as a result of living in high-trust communities; rather, there was a somewhat detrimental effect of community trust on the self-rated health of such individuals.

These novel findings on the relative influences of individual and community influences of social trust on health argues for the need to conceptually refine the role of social capital in shaping population health. Previous discussions have tended to emphasize the notion that higher levels of community social capital are health enhancing for everyone, regardless of their individual characteristics.<sup>1,7</sup> More recent contributions have cautioned against the simplistic approach that views social capital as a panacea for public health, citing the potential “downsides” of social capital.<sup>4,5,20</sup> The important downsides of social capital include phenomena such as restrictions on individual freedom imposed by an excessively cohesive social milieu; the down-leveling of social norms caused by pressures to conform; and the excessive obligations placed on members of a cohesive community to supply the “goods” associated with social capital (for example, in the form of voluntarism, community participation, and the provision of social support).<sup>2,4</sup>

The preliminary evidence in our study supports the view that community social capital is not uniformly healthy. Community social capital may be a “good medicine” only for those who express high levels of trust or who value trustworthiness in others. There is some plausibility for suggesting that low-trust individuals fare worse in high-trust communities. Perhaps low-trust individuals (or individuals who prefer to remain apart from their fellows) feel ostracized, alienated, or put upon as a result of residing in communities in which others feel and act the opposite. Such complex interactions would benefit from more in-depth investigations, perhaps through ethnographic approaches.

In addition to the above, our findings raise interesting issues related to the “compositional” and “contextual” aspects of spatial community variation. One of the key advantages of a multilevel statistical model is its ability to estimate the between-community variation. Put simply, a significant variation between communities provides us with a clue about the influence of community contexts in shaping health patterns. Importantly, it helps us to establish whether the community differences in self-rated health are due to the characteristics of the people who live in these communities (compositional variation in communities) or due to factors that relate to communities themselves (contextual variation in communities). For instance, based on the final individual model results (Table 2, model 2B), it is clear that, once we take into account the individual compositional effects of socioeconomic status, communities do not make a difference to poor self-rated health.

These findings, however, do not necessarily suggest where people live is not important to how they perceive their health. As the analysis suggested, the contextual differences remained significant even after including individual sociodemographic factors such as age, sex, race, and marital status. Thus, it is only with the

inclusion of socioeconomic factors such as educational attainment and income that the between-community variation became statistically nonsignificant. Arguably, the ability of an individual to earn a particular level of income or attain a particular level of education is itself dependent, among other things, on “where they live(d)”; therefore, to view them as purely individual covariates is debatable.<sup>21</sup> Individuals often choose to live in particular communities to obtain better education or access to higher-paying jobs. Furthermore, the lack of community variation need not necessarily mean absence of a contextual effect. Indeed, it is possible to “mis-specify” a statistical model by omitting a “relevant” variable at the contextual (community) level. The statistically significant effect of the community trust (model 3) and complex cross-level effect of social trust (model 4B) substantiate the above statement and compel us to develop contextual lines of explanation.

While not reported here, we also tested for the nonlinear effects of community trust on self-rated health using a polynomial (squared) term for the community trust variable. There was some evidence for a nonlinear relationship between individual health and community trust, with an inverse U-shaped curve. However, the observed nonlinearity seemed to be an artifact of (1) not considering individual trust perceptions in the model and (2) not considering the interaction between individual trust perception and community trust. Investigators have seldom examined such nonlinearity in neighborhood effects (including social capital). Yet, “tipping points” may exist.<sup>22</sup> For example, neighborhoods vary little in teen pregnancy rates and school dropout rates when the proportion of residents with high socioeconomic status varies between 5% and 40%. However, when the proportion of professionals drops below 5%, rates of both problems have been observed to double.<sup>23</sup> In a similar manner, there may be a threshold level of social trust below which health effects begin to be observed. Although we did not find a significant nonlinear effect in this particular instance with a squared polynomial function, the motivation was to move beyond linear estimation techniques that may miss the presence of nonlinear and/or threshold effects that could be specified using other statistical functions.<sup>24</sup>

### Limitations

Our study had a number of limitations. First, the study was cross sectional, so that reverse causality cannot be ruled out (i.e., worse health status leading to lower perceptions of trust). Second, individuals do not randomly locate to different communities. There is an inevitable element of self-selection by individuals in terms of where they choose to live. For example, high-trust individuals may choose to move to certain communities because they prefer to live in proximity to trustworthy neighbors. Analyses of observational data—even with the use of corrective approaches such as instrumental variable analysis—are unlikely to succeed completely in removing this type of endogeneity. The demonstration of a convincing causal effect of social capital on health may require innovative strategies, including randomized community-level research designs and intervention studies.

Our study was quite limited in its assessment of social capital. We focused on only one indicator of the concept, social trust. Other indicators have been used in the literature, including collective efficacy, measures of reciprocal exchange, voluntarism, and informal sociability.<sup>3,4,10</sup> Accordingly, the evidence presented here with regard to the cross-level interaction between community and individual trust should not be taken to mean that similar effects exist for other dimensions of social capital. Rather, our findings stress the need to explore such connections empirically for the other important dimensions of social capital that have been used in public health.

As observed in our analysis, once we considered the individual perceptions of trust, the white-black differential in self-rated poor health was altered, rendering it statistically insignificant. Research on social capital and population health has yet to investigate the racial dynamics associated with this relationship. While developing this was beyond the scope of our article, we consider this as a potentially important area for further exploration, especially with regard to developing causal explanations between community social capital and individual/population health.

## CONCLUSION

In this article, we elucidated the relative contributions of individual and collective/community social trust on self-rated health. Our findings suggest that the association is more complex than described previously. Our findings point to the need for more nuanced theory and meaningful multilevel investigations of the effects of social capital on population and individual health.

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